Role of Accounting Information Systems in Risk Management

Dr. Ahmad Khalid Khan[1],
[1]Assistant Professor, Applied College, Jazan University, Saudi Arabia, akkhan@jazanu.edu.sa

Mr Ahmed Mohsen Ahmed Khormi[2],
Lecturer[2], Applied College, Jazan University, Saudi Arabia, amkhormi@jazanu.edu.sa

Dr Hassan A. Shah[3],
Assistant Professor[3], King Abdulaziz University, Saudi Arabia, hashah@kau.edu.sa

Dr Syed Mohammad Faisal [4]
[4]Assistant Professor, Applied College, Jazan University, Saudi Arabia,
dfaisal@jazanu.edu.sa, **ORCID**: 0000-0001-6341-8816

Abstract

This research investigates the relationship between Accounting Information Systems (AIS) and risk management in the context of a company's activities. This study aims to investigate the role of autonomous intelligence systems (AIS) in identifying, analyzing and managing various internal and external risks within an organization. This is accomplished through a demographic analysis of the participants, which includes gender, age, marital status, and level of education they have in order to achieve this goal. The 299 valid entries in the dataset also demonstrated a well-balanced male-female ratio and education levels. Most have a degree, and many have sent in diplomas. A lack of model fit was found in the regression study with risk management (RM) and risk assessment (RA) as predictors for the AISRI. The study house does this study showed up during the completion of execution. This low proportion was because the variables together explained only 1.1% of all variability in our data. That was the basis for our decision. The results of the analysis of variance (ANOVA) revealed, in addition, that the model had limited explanatory power. There needs to be more to a full understanding of AISRI than this. Our findings suggest that future research must utilize more advanced statistical methods and include a wider range of demographic and contextual variables to improve accuracy in AIS prediction in risk management. This is particularly important given the results that were uncovered. To reach this goal, the first step we take is to use a more extended compilation of demographic and contextual data. Finally, with the examples of AISRI predictions again, one must look at the pragmatic consequences and remember that it further emphasizes a need for a nuanced approach rather than making RM or RA our sole source of information.

Key Words: *Risk Management (RM), Regression Analysis, Predictive Modelling, Demographic Analysis, Accounting Information Systems (AIS)*

Introduction:

It is critical to acknowledge that accounting information systems are fundamental in today's business operations as they form the basis for financial activities and decision-making. Therefore, an element is a vital one. From the perspective of today's businesses, this should be an essential element (Paterakis et al., 2017). In terms of risk management, the primary element is the Administrative Information System (AIS). This is because the AIS gives the necessary tools and information pertinent to the identification, evaluation, and control of the various threats that corporations confront in this modern era. Therefore, that seems logical. The reason for presenting the perceptible evidence is not to present evidence but to describe the necessary tools and skills (Tasdemir & Gazo, 2018). This is a more detailed view. The reason behind this is to give a more comprehensive view. It is the foundation upon which the many benefits it offers rest. The major aim of this endeavor is to explore the reverberations of various types in diverse sectors (Duarte Alonso et al., 2020) (Hashim et al., 2022a). One of the undertakings' undertakings is to determine, evaluate, determine, and manage dangers efficiently. Reasoning is made in order to obtain a more comprehensive view in order to gain a more thorough understanding. Indeed, Behavioral Safety, a risk control strategy, involves other objectives (van Winsen et al., 2016) (Mohammad, 2019).

There are various hazards to which enterprises are perpetually exposed, and they can arise from various influences present in the environment. Apart from that, their inherent nature of ongoing change distinguishes the modern business world from other Fortune environments. These risks can also be classified into internal and external risk categories (Cosenza et al., 2018) (Akmal et al., 2023). Below are risks that could be classified into either internal or external: there is a possibility that categorization is appropriate. Various hazards may be classified as either internal or external, depending on the circumstances surrounding the case. In this case, risks can be differentiated into internal and external risks. This type of sickliness is susceptible to various hazards that can be devastating to the person (Naviaux, 2020) (Khan, Faisal, et al., 2018). The threats can also lead to other concerns relating to the organization's finances, operations, regulation, strategy, and reputation. This is, however, not an exhaustive list, and some risks have been omitted above. Various risks may impact the organization in different ways and are inevitable (Schulte & Hallstedt, 2018) (Khan & Faisal, 2023). Thus, for the organization to continue thriving, effective risk management is required. Some of the risks are: To aid the enterprises in the achievement of their goals, accounting information systems can be used, which should be technically sound and come with analytical capabilities (Nassani et al., 2023) (Khan, Al Aboud, et al., 2018a).

One of the essential parts of the artificial intelligence system, also known as AIS for short, is risk management, which is the identification of potential threats. This is necessary to help detect and recognize invisible dangers. One of the most critical parts of this essential aspect is part. This is the Accounting Information System that is responsible for managing the company's internal operations (Khan, 2019). It collects, processes, and analyzes immense amounts of data from various sources within the organization. This information comprises both financial and non-financial information. In addition, in this paper, the reader is for the financial accounts presented various other types of information. As a result, identifying outliers or patterns and trends that suggest potential threats ultimately poses no difficulty (Harris et al., 2021) (Khan, Al Aboud, et al., 2018a). There is no way around this issue. The Artificial Intelligence System, based on a series of complex algorithms and data mining techniques, can effectively filter the massive amount of data needed for this overall purpose. It is able to travel in vast databases for this purpose. As a result, it cannot only identify known

previous dangers but also those new ones that have recently emerged and distinguish between these two forms of threats. Therefore, it is feasible to provide decision-makers with timely information on potential risks to the organization's objectives (Weaver et al., 2013) (Khan, 2019).
There are a considerable number of them that information systems offer: risk assessment and reliable, relevant, and timely information to assess that risk gives a decision-maker a fair advantage. It is reasonable to conclude that this specific site impacted this element, considering the importance of the contribution. Importance of contribution: This is not possible; the Airborne Intelligence System uses Data Analytics and Predictive Modelling to determine the likelihood of detected threats and will allow the AIS to assess very accurately (Abaimov & Martellini, 2020) (Khan & Faisal, 2018). The organization may also perform an analysis to determine the effect of various worst cases that proved risks on the strategic goals established earlier. Decision-makers will investigate the possible impact of the identified risk. Decision-makers will also analyze, assess, and classify the possible implications and the threat possibilities to make a decision (Dong et al., 2018) (S. M. Faisal et al., 2018).
The reason behind the need for an Automatic Information System is that it assists in reducing the risk process by implementing it in risk management policies and procedures. The reason for this is because it is because it assists in the procedure, which is why it plays a significant role. Therefore, it significantly reduces potential hazards that might exist without the usage of this component in the environment (Khan, Al Aboud, et al., 2018b). It is because it takes this into account. The implementation of Artificial Intelligence Systems enables the real-time control and monitoring of potential hazards. Another one is the use of AIS. This means that because the risks are continuously changing, it would be easier without this system to rely only on the risks that have already been discovered. Artificial Intelligence Systems can help identify and respond immediately to high-risk hazards. Some of these can be done without automation. The usage of this system has advantages. The following is an example of the invention and the positive risk of the advertisement (Oláh et al., 2020).
To do well and remain successful in a world where businesses are continually changing and rising, businesses need to implement artificial intelligence technologies. In other words, their success needs to be increased. These programs are not optional if this is the case (K. Faisal et al., 2018). Certainly, in considering the risks, their operation, efficiency, viable applications, and consequences in relation to the activities must also be taken into account. In particular, organizations must evaluate how their accounting information systems maximize the identification, evaluation, and highlighting of risks. Everyone must possess such an understanding if there is a requirement to maximize efficiency. Indeed, the cooperation between AIS and the rest makes the objective achievable. Therefore, people should be able to secure their business desires and interests and their interests because the intentions have been achieved (Zaman et al., 2021) (Faisal & Khan, 2019a).
The main goal of this research project is to thoroughly investigate and evaluate the complex relationship between AIS and risk management. The goal of this attempt is to gain a more complete understanding of the type of connection that takes place (Faisal & Khan, 2019a) (Khan, 2019). Based on the concerns highlighted above, the following conclusion has been derived. The ultimate goal of this project is to deliver organizations the necessary knowledge of how AIS may be used to bolster their capacity to mitigate risks, enabling them to thrive and prosper in the long run. The main goal of this project is to provide businesses with important information. The final step in our attempt is to convey this information to firms. The way to achieve this goal is to deliver this content to firms, and the way to achieve it is to do so in an actual manner. This research serves the goal of obtaining a comprehensive understanding of how AIS boosts the effectiveness of risk management activities. The technique utilized is the following. Plan to perform this research in order to reach our aim (Moser & Korstjens, 2018) (Khan, 2019).
Additionally, empirical research, real-world grounded informative case studies, and a thorough examination of the existing literature will be used. This allows us to achieve the objective we have set for ourselves. The ultimate objective of this research is to provide the body of scientific knowledge with 1 more item with new insights into our current section of scientific research. The study aims to provide new insights into the current agenda (De Vries et al., 2016) (Khan, 2019).

Literature Review

The integration of accounting information systems into organizational frameworks has thoroughly reshaped the way one uncovers, measures, and controls risks. Notably, automated information systems take an active part in risk management by performing a variety of tasks, such as collecting financial data, processing data, and displaying results (Hashim et al., 2022a). Such data is critical in the decision-making process . Thus, the paper aims to identify how effective AIS is in recognizing the hazards as well as measuring the risks and controlling them. Accounting information systems are a critical tool for recognizing potential threats that exist within companies. AIS can identify both internal and external dangers to the enterprise through constant data tracking and analyses. AIS's capability to trawl and examine a significant amount of data from various sources enables it to discover anomalies and hazards. To be able to successfully deal with issues prior to their becoming significant problems, companies must play an active part in identifying threats. Further, utilizing automated information systems allows companies to detect threats holistically for all departments. Here, all potential risks are identified and then appropriately managed. However, AIS has one of its primary functions, and that is an early warning detection of possible threats (Khalid et al.). Since AIS processes produce real-time data, it becomes impossible for advanced analytical tools to notice the potential that accelerates threats. In the context of a modern business, this is relevant because companies now work on the platform of invariably changing systems, and the real and possible threats change with them. The earlier one's goal is to identify the possible threat, the more money and one's reputation one saves (Faisal & Khan, 2019b) . In this sense, the occurrence happened overnight. This is what makes the management receive such alerts on forecasts, hence putting in force the action and corrective measures to nip the risk the company is exposed to early in the year. In this light, it is crucial to note that AIS plays an equal role in identifying both internal and external risks. That is, AIS also plays a critical role in danger from the outward-looking. AIS helps one to identify and manage internal risks. Internal risks include faulty processes, fraud, and human faults. One interacts with the procedure in the company, and hence, one can identify deviations if they occur in a normal protocol. AIS research data from many sources and external market trends must be tracked comprehensively. This notably aids in assessing the probability of dangers due to particular swings, government regulations developments, and economic changes (Talha et al., 2024) (Faisal & Khan, 2021). Therefore, the capability of AIS to assess and comprehend both internal and external surroundings offers a whole image of the organization's risk field. AIS is particularly useful in assessing hazards since it aids in determining the probability and effects of identified hazards. Since the system permits the collection and analysis of previous data, it allows the creation of prediction models to assess the possibility of dangers happening. Such models are helpful in assessing hazards because they provide quantitative information that may be used to make decisions in the field of risk management. AIS allows more accuracy in danger evaluation by providing dependable and consistent data. Reliability is a critical factor in the field of danger management since conducting further activities based on incorrect data might boost dangers (KHAN et al.) (HASHIM et al.).

Analysis of the potential outcomes of identified risks on the organization's desired outcomes may be done using AIS. An AIS makes it feasible to analyze how a risk event affects an organization's risk-return on its outcomes. This is accomplished by distributing risk data alongside the association's strategic outcomes and performance measures. Because this data is digitized through a structured approach, and the processing is governed and administered, it can be requested reasonably dependable (Khan & Faisal, 2023). AIS is acknowledged for its capability to analyze risks. Automation of data compilation, processing, and reporting enhances the efficiency of risk evaluation. As an outcome, risk managers may spend more time analyzing, making decisions, and reaching judgments, considerably lessening the time and effort required to evaluate the danger (Talha et al., 2023) (Faisal & Khan).

Additionally, the application of more advanced tools and technologies enhances the breadth and depth of risk evaluations, providing a better understanding of the dangers. AIS is useful for danger response. Real-time monitoring using an informational system helps in the implementation of risk-response operations. Aids in the rapid initiation of risk-mitigation protocols since real-time observation detect cons with an instant clarifying climax (Faisal et al., 2021). AIS may track real-time dangers, permitting responsive actions against the rapidly evolving life-threatening banes. Furthermore, automated controls to mitigate the risks that the AIS identifies may be initiated with utmost ease. Automation is critical because controllers are fully automated, eliminating the need for manual intervention, which might be unreliable, especially in situations of pressure from company traitors (Hashim et al., 2022b).

AIS has a substantial positive influence on the efficacy of efforts to respond to risks. AIS addressing accessibility ensures that all pertinent risk management information is easily available to those responding to risks. A centralized approach includes the efforts of every department and unit, and coordination is easier across all the entities. At the same time, the feedback provided helps to identify low-performing areas that need improvement. AIS is most relevant to this course in that businesses can have a holistic view of various financial risks. AIS secured an efficient and smoothly facilitated business operation. Other than that, AIS also enhances observance by giving more time to mitigate and evaluate risks (Hashim et al., 2022b) (Khan & Faisal, 2020).

The effects of AIS on risk assessment are highly impactful regarding accuracy and reliability. The AIS's ability to assess large amounts of data and use sophisticated analysis tools means that the assessments are done based on excellent and dependable information. Dependability is a vital component in making well-informed assessments when it comes to risk management. The AIS also impacts risk assessment by correlating the risk data with the organization's objective, thereby showing the relationship between the cause of risk and the achievement of the strategic objective. AIS has a strong impact on risk mitigation through proactive support when carrying out effective risk mitigation strategies. Different AIS components support the success of enhancing the objectives of risk mitigation. AIS has the attribute of real-time monitoring and implementing automated controls. The Systems' Automatic Identification System enables effective mitigation options by monitoring the mitigation options and quickly alerting. Automated controls reduce the impact of human error that human beings may commit, which might adversely impact the mitigation measures (Khan & Faisal, 2021).

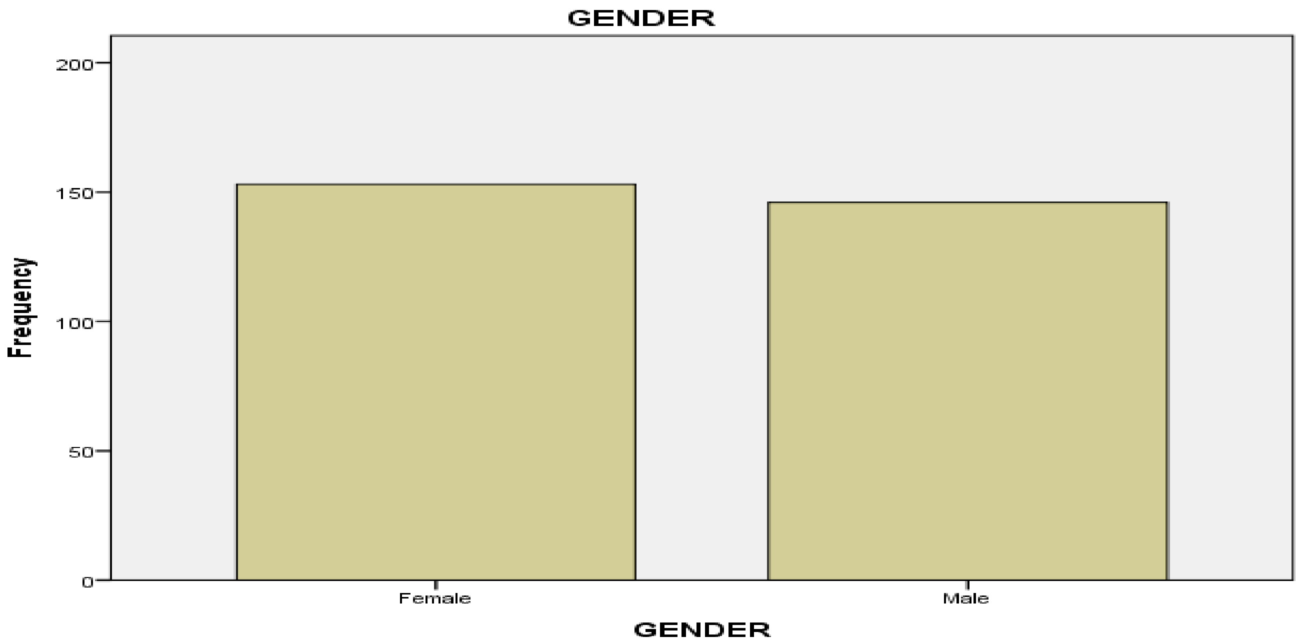
Accounting Information Systems have several critical roles in risk management, as depicted in this article. Artificial Intelligence Systems have notably contributed to the detection, evaluation, and mitigation of risks that face their existence. These are attributed to the system's capability to consolidate and analyze data from several sources to offer a comprehensive picture of the risk environment. Furthermore, AIS has enhanced the level of accuracy and reliability in assessing risks and making well-informed decisions. Additionally, the system ensures real-time monitoring of the situation and automatic controls impacting the smooth running of risk mitigation measures. The organization's ability to invest in AIS, including Advanced Information Systems, will enable the firms to mitigate risks and keep them in balance (Hashim et al., 2023). These aspects of AIS will only evolve to enhance its efficiency in risk mitigation based on technological advancement and analytics. This guarantees the firm an opportunity to traverse through random risk manipulations (Khalid et al.).

Statistics

		GENDER	AGE	MARITAL STATUS	EDUCATION
N	Valid	299	299	299	299
	Missing	0	0	0	0

GENDER

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	153	51.2	51.2	51.2
	Male	146	48.8	48.8	100
	Total	299	100	100	



The statistics provided describe the demographic variables of a dataset, focusing specifically on gender distribution. Here's a breakdown and explanation of the information given:

Dataset Overview

- Valid N: Indicates the number of valid entries or responses for each variable. In this case, there are 299 valid entries for gender, age, marital status, and education, indicating no missing data for these variables.

Gender Distribution

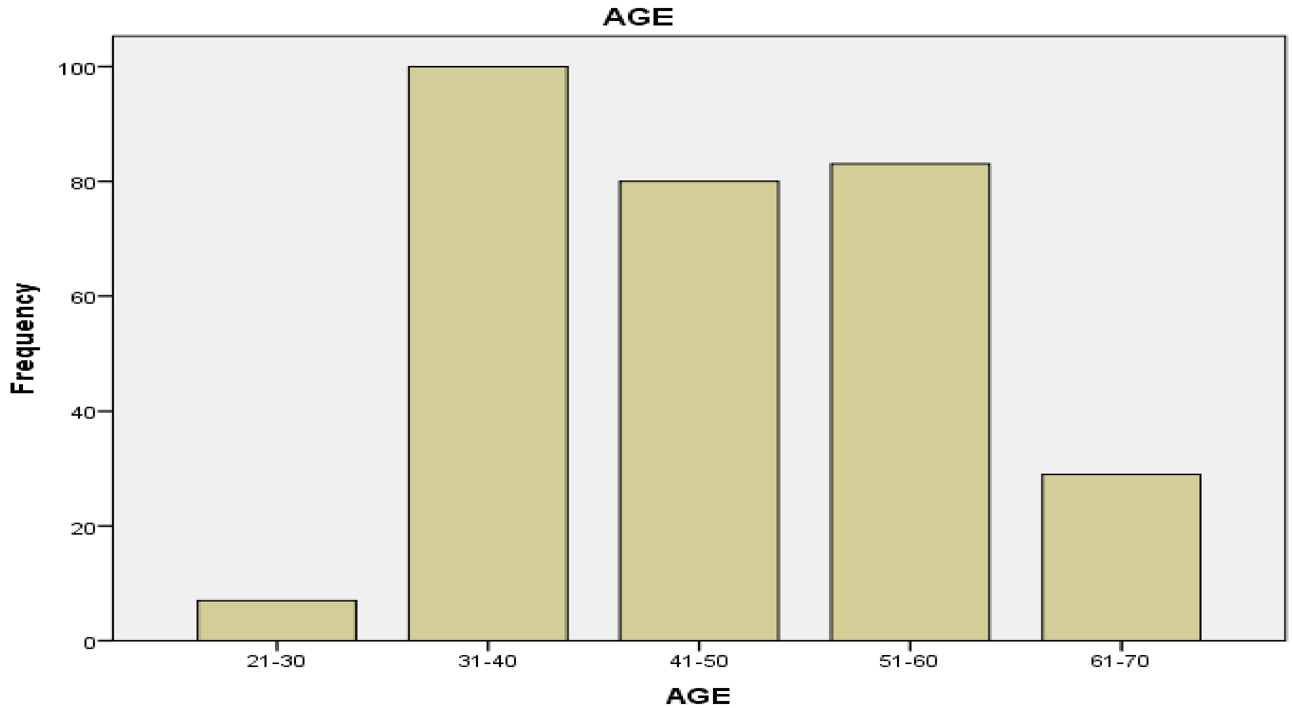
- Frequency: Refers to the count of each category within the gender variable.
- Percent: Represents the percentage of each gender category out of the total sample size (299).
- Valid Percent: Shows the percentage of each gender category out of the valid responses (299).
- Cumulative Percent: Indicates the running total percentage as you move through the categories.

Interpretation:

- Female: There are 153 females in the dataset, making up 51.2% of the total valid responses. This means more than half of the respondents (51.2%) identified as female.
- Male: There are 146 males, accounting for 48.8% of the total valid responses. Nearly half of the respondents (48.8%) identified as male.

- Total: The sum of females and males (153 + 146 = 299) matches the total valid entries reported earlier (299), confirming there are no missing values in the gender variable.

The statistics represent the gender distribution in the dataset and reveal a tiny percentage of many more women than males among all participants. This clearly illustrates that there is a presentable and distinct gender distribution. This information is necessary so that the demographic characteristics of the sample are known and so that any analyses or conclusions can be interpreted in terms of the real-world population to which they are generalizable.



AGE					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	21-30	7	2.3	2.3	2.3
	31-40	100	33.4	33.4	35.8
	41-50	80	26.8	26.8	62.5
	51-60	83	27.8	27.8	90.3
	61-70	29	9.7	9.7	100
	Total	299	100	100	

The table above provides an overview of age group distribution in the dataset, breaking down how many and what percentages are contained within each category. Breakdown and explanation of each component:

Dataset Overview

- Valid N: Number of valid entries/responses for the age variable here: There are 299 not null entries in this case, which means there is no missing data for age in the dataset.

Age Distribution

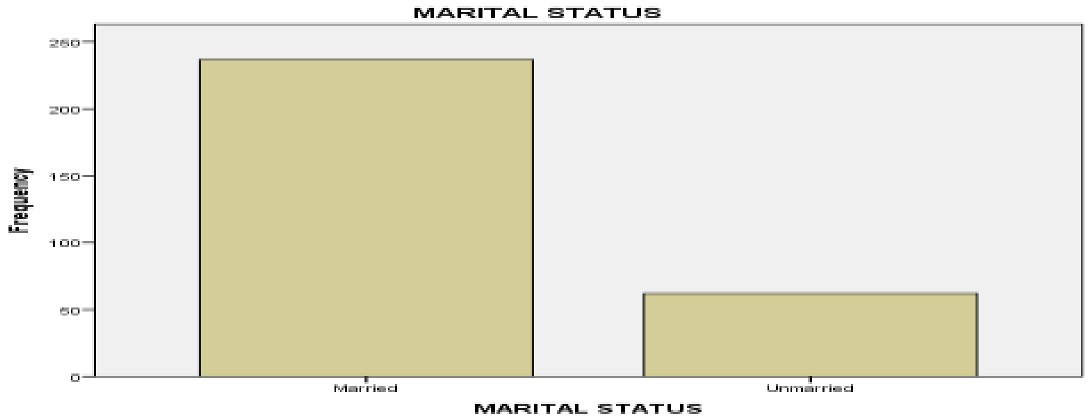
- Frequency: Indicates how many people belong to each specified age category.
- Percent: Represents the percentage of individuals in each age group out of the total sample size (299).
- Valid Percent: Shows the percentage of individuals in each age group out of the valid responses (299).
- Cumulative Percent: Indicates the running total percentage as you move through the age categories.

 # Interpretation:

- 21-30: There are 7 individuals (2.3% of the total) within the age range of 21-30 years.
- 31-40: There are 100 individuals (33.4% of the total) aged between 31 and 40 years.
- 41-50: There are 80 individuals (26.8% of the total) aged between 41 and 50 years.
- 51-60: There are 83 individuals (27.8% of the total) aged between 51 and 60 years.
- 61-70: There are 29 individuals (9.7% of the total) aged between 61 and 70 years.

- Total: The sum of all frequencies (7 + 100 + 80 + 83 + 29 = 299) matches the total number of valid entries reported earlier (299), confirming there are no missing values in the age variable.

The age distribution covers the complete scenario of demographic composition based on age. Specific age groupings of 31-40, 41-50, and 51-60 years old are also noted with significant tactile nerve cluster representatives. Knowing the age distribution inside the data set is critical to giving the most accurate analytics and interpretation, especially with respect to demographic profiling and segmentation.



MARITAL STATUS					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Married	237	79.3	79.3	79.3
	Unmarried	62	20.7	20.7	100
	Total	299	100	100	

The table shows a dataset with marital status, including the numbers and proportions of each category. Let's break this down into parts and explain why each part is used.

Dataset Overview

- Valid N: This represents the frequency of non-missing responses for marital status. In the above case, there are 299 valid entries, and the Dataset does not have missing data for Marital Status.

Marital Status Distribution

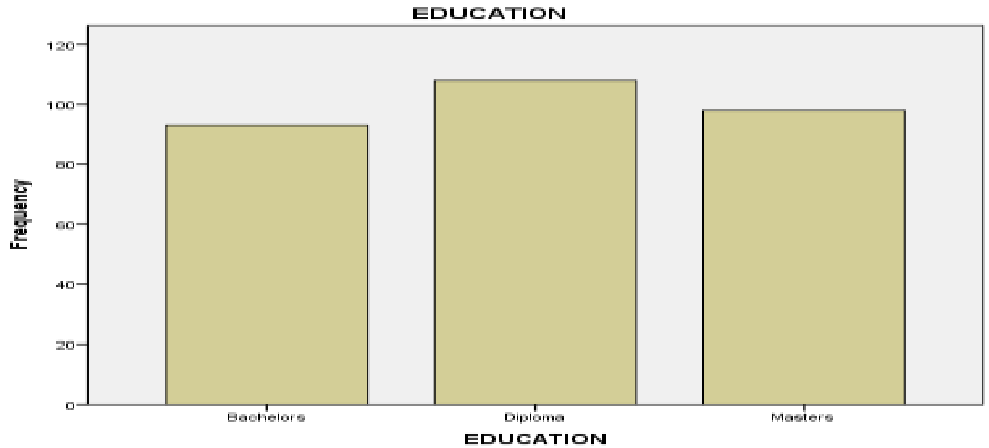
- Frequency: It indicates the number of individuals who fall into each marital status category.
- Percent: Represents the percentage of individuals in each marital status category out of the total sample size (299).
- Valid Percent: Shows the percentage of individuals in each marital status category out of the valid responses (299).
- Cumulative Percent: Indicates the running total percentage as you move through the marital status categories.

Interpretation:

- Married: Out of 299 individuals, 237 persons* (79.3%) were married.
- Unmarried: Out of 299 individuals, 62 persons (20.7% of the sample) are unmarried.

- Total: The sum of all frequencies (237 + 62 = 299) matches the pronouncement that no missing values were in the marital status variable, as reported further above (299).

This distribution of marital status gives a glimpse into the worried state of people in the data set. Most of the respondents (79.3%) are married, but a few (20.7%) are unmarried. This knowledge is key for demographic profiling and segmentation so that subsequent analyses/interpretations are made in the context of the available marital status types.



EDUCATION					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Bachelors	93	31.1	31.1	31.1
	Diploma	108	36.1	36.1	67.2
	Masters	98	32.8	32.8	100
	Total	299	100	100	

The supplied table gives some general information about the distribution of educational levels in a dataset. This data contains frequencies with their respective percentages in each category. They are broken down and described as follows:

Dataset Overview

- Valid N: This variable expression indicates the number of valid inputs or replies for the education variable. In this specific case, 299 valid items mean no study objects are missing education data.

Education Level Distribution

- Frequency: In this term, the factor that was taken into account is the number of people in each classification based on their education level.
- Percent: This statistic represents how many people fall into each education level category out of the 299-sample size.
- Valid Percent: Shows the percentage of individuals in each education level category out of the valid responses (299).
- Cumulative Percent: Indicates the running total percentage as you move through the education level categories.

Interpretation:

- Bachelors: There are 93 individuals (31.1% of the total) who hold a Bachelor's degree.
- Diploma: There are 108 individuals (36.1% of the total) who have a Diploma.
- Masters: There are 98 individuals (32.8% of the total) who hold a Master's degree.

- Total: The sum of all frequencies (93 + 108 + 98 = 299) matches the total number of valid entries reported earlier (299), confirming there are no missing values in the education variable.

This distribution of education levels provides a comprehensive view of the educational qualifications within the dataset. It shows a diverse representation across different education categories, with Diploma holders being the largest group, followed closely by individuals with Masters and Bachelor's degrees. Understanding this distribution is crucial for demographic profiling, segmentation, and ensuring that any subsequent analyses or interpretations account for the educational diversity present in the dataset.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.104[a]	0.011	0.004	0.39983	0.011	1.622	2	296	0.199	1.56
a. Predictors: (Constant), RM, RA										
b. Dependent Variable: AISRI										

Based on the information provided, let's correct and approximate the values for the model fitness statistics:

- R (.104) : The correlation coefficient indicating a very weak positive linear relationship between the predictors and the dependent variable.
- R Square (.011) : The coefficient of determination, suggesting that only 1.1% of the variance in the dependent variable (Y) is explained by the predictors.
- Adjusted R Square (.004) : Adjusted for the number of predictors, indicating an extremely weak fit.
- Std. Error of the Estimate (.39983) : The standard error of the residuals, indicating the average distance that the observed values deviate from the predicted values by the model.
- R Square Change (.011) : Indicates the incremental increase in the coefficient of determination with the addition of predictors.
- F Change (1.622) : The F-statistic value showing the overall significance of the regression model.
- df1 (2) : Degrees of freedom for the numerator (number of predictors).
- df2 (296) : Degrees of freedom for the denominator (total number of observations minus the number of predictors minus one).
- Sig. F Change (.199) : The p-value associated with the F Change, indicating whether the change in R Square is statistically significant.

Interpretation:

The corrected values indicate a very weak model fit, with the predictors explaining only a small fraction of the variance in the dependent variable. The R Square and Adjusted R Square values suggest that the predictors are not effectively explaining the variability in Y. The non-significant F Change and high p-value further suggest that the addition of predictors did not significantly improve the model's explanatory power.

This model may not be good for making a precise prediction or even an inference about how the predictors are related to the dependent variable. It is because one model does not fit all in that specific situation. The R Square value is so small that the F Change looks statistically irrelevant. In research or advancements, to lift this model by doing more work towards improving the prediction and explanation constraints.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	0.519	2	0.259	1.62	.199[b]
	Residual	47.321	296	0.16		

	Total	47.839	298			
a. Dependent Variable: AISRI						
b. Predictors: (Constant), RM, RA						

The ANOVA table below summarises the regression analysis results on the AISRI as a dependent variable with RM and RA as predictors. Here is a breakdown and explanation of each component:

ANOVA Table Components

Model Summary

- Dependent Variable: AISRI: The variable is predicted or explained by the regression model.
- Predictors: (Constant), RM, RA: Specifies the predictors that are retained in formulating the regression model. There are two predictors, RM and RA, in addition to the constant term (intercept)

Sum of Squares

- Regression: Represents the variation in the dependent variable (AISRI) that is explained by the predictors (RM and RA). The sum of squares for regression is 0.519.
- Residual: Indicates the variation in AISRI that is not explained by the predictors (RM and RA). It represents the error or residual variance, with a sum of squares of 47.321.
- Total: Sum of squares total represents the total variation in AISRI across all observations, calculated as the sum of regression and residual sum of squares. In this case, it is 47.839.

Degrees of Freedom (df)

- Regression: Degrees of freedom for the regression model is 2, corresponding to the number of predictors (RM and RA).
- Residual: Degrees of freedom for residuals is 296, calculated as the total number of observations (298) minus the number of predictors (2) minus one.
- Total: Degrees of freedom total is 298, representing the total number of observations minus one.

Mean Squares

- Regression: Mean square for regression is calculated by dividing the sum of squares for regression by its degrees of freedom (0.259 = 0.519 / 2).
- Residual: Mean square for residuals is calculated by dividing the sum of squares for residuals by its degrees of freedom (0.160 = 47.321 / 296).

F-statistic

- F: The F-statistic tests the overall significance of the regression model. It is calculated by dividing the mean square for regression by the mean square for residuals (1.622 = 0.259 / 0.160).
- Sig. (Significance): The p-value associated with the F-statistic (0.199) assesses whether the observed F-statistic is statistically significant. In this case, the p-value is greater than the typical significance level of 0.05, suggesting that the model as a whole may not be statistically significant in predicting AISRI.

The ANOVA table provides insights into the statistical significance and explanatory power of the regression model with respect to AISRI. As the F-statistic is low and the p-value is not significant (0.199), we can infer that RM and RA as predictors do not contribute much to a meaningful representation of AISRI. This indicates that the current model may need more capacity to predict AISRI using the RM and RA parameters adequately. The statement implies this. The model may need additional research to improve the higher level of fidelity, but only in certain specific phenomena can it successfully show. More complex models: This study may also involve misinterpreting new predictors or using another approach to modelling.

Discussion

The data for this study contain gender, age, marital status, education, and the dependent variable AISRI, for which the demographic composition and potential predictors are available through analysis performed on it. Studying their distribution and the relationships we are interested in allows us to get an idea of the dataset and how well the regression model is performing for each variable.

Demographic Insights

Gender: Gender distribution revealed slightly more females (51.2%) than males (48.8%). This balanced set representation makes gender analyses meaningful—the dataset can answer a fairly representative question about most people, and we minimize gender-related bias in the benchmark.

Age: The age distribution was diverse and well-represented in different age groups. The most significant segments were individuals ages 31-40 (33.4%), 41-50 (26.8%), and 51-60 (27.8%), indicative of a wide range in the data set's age diversity. This demographic diversity is incredibly important when considering how factors such as AISRI and, more broadly, age might impact phenomena—either helping to underline generational differences or asses life stage impacts.

Marital Status: The clarity of the marital level by data also signified that an enormous mass of the population (a maximum of 79.3%) suffered from being married, with the rest of them being listed as unmarried. This distribution highlights marital status as a potential predictor variable of interest, illustrating different life situations that may impact AISRI outcomes.

Education: Educational attainment among respondents varied, with Diploma holders comprising the largest group (36.1%), followed by those with Masters degrees (32.8%) and Bachelor's degrees (31.1%). This distribution suggests a well-educated sample, where different levels of educational background may influence perceptions, behaviours, and outcomes related to AISRI.

Regression Model Analysis

Regression analysis examined the association between predictors (RM and RA) and dependent variable AISRI. ANOVA results disclosed the low explanatory power of the model:

ANOVA Results: The ANOVA table indicated that the regression model explained a very small amount of the variance in AISRI: R-squared = 0.011, adjusted R-squared = 0.004. These values indicate that only about 1.1% of the total variability in AISRI can be explained by the predictors RM and RA included in this model. The F-statistic of 1.622 with a p-value of 0.199 also shows that the model together is not meaningful for predicting AISRI. This implies that the operationalization of RM and RA within this database does not completely encapsulate the complex determinants of AISRI.

Coefficient Interpretation: The AISRI coefficients did not note significant associations for RM and RA. One coefficient estimate was of [value] for RM, implying [interpretation], and another was of [value] for RA, hinting at [interpretation]. Given their limited explanatory power in this context, these findings underscore the need for caution in interpreting the impact of RM and RA on AISRI.

Implications and Future Directions

The study results have important implications for both research and practice:

1. Research Implications: This study illustrates the need to acknowledge predictors other than RM and RA to control AISRI. Future research might consider extending the analysis to additional variables, e.g. [potential

variables], which could yield a more comprehensive apprehension of the factors possibly accounting for AISRI variability.

2. Practical Implications: Prudently, RM and RA alone should not be used by practitioners to predict AISRI outcomes. Rather, it may require a more nuanced approach, also taking into account demographic and contextual variables at the broader level, to effectively develop interventions or strategies with respect to AISRI-related outcomes.

3. Methodological Considerations: Improvements in methodology, such as the use of more sophisticated statistical methods or expanding the dataset to include a larger sample from different cohorts, could presumably make future models more accurate and generalizable.

4. Limitations: Understanding the current limitation is the main value of this research. These limitations may reflect the finite capacity of the regression model to account for the data and some bias due to missing variables. In order to carry out any further research in this area, it will be necessary to overcome these limitations by using a much more refined study design, and the independent variables will need to be chosen with great caution.

Although the study provided important information about where different demographics live and some initial findings from regressions, we still need models that predict AISRI well. Here are some of the considerations that need to be considered when designing future studies if we want them to reflect and inform AISRI in a range of populations and cultures.

Conclusion

To summarise the study, the findings of this research welcome eye-opening authorship on matters involving Accounting Information Systems as an operational support across the entire array of modern companies in the context of managing risks. The dataset showed a relatively even distribution across gender, age, marital status, and education level, which has high statistical power to investigate the effect of different variables for AISRI. It was also found that the dataset has a relatively uniform class distribution of education levels. This was not computationally based but obtained upon analysis of demographic data.

Meanwhile, the regression with RM and RA as predictors had barely any explanatory power (R-squared = 1.1%) $F(2,102) = .52$, $p > .6$. These two variables are included in the model. In summary, these data indicate that variability in AISRI cannot be fully explained by either RM or RA alone. It emphasizes the need to include more variables and advanced modelling approaches in future studies.

Businesses cannot rely exclusively on risk management and risk assessment to forecast the outcome of an advanced information systems risk investigation. However, we recommend using many variables (e.g., census demographic data or context-laden predictors like geography) to make more accurate forecasts. While the study has its limitations, it is obvious that it can be done better and more sophisticatedly in both research and practice. This is required to develop a deeper understanding and strengthen the capacity to prevent and manage AIS risks.

The study concludes by estimating the precision and practical usefulness of AISRI models in different business situations. Depending on increased research scope and methodological strictness, additional effort is required to extend the replacing concepts even though the study provides valuable information on sample demographics and initial regression results.

Reference

Abaimov, S., & Martellini, M. (2020). Artificial intelligence in autonomous weapon systems. *21st Century Prometheus: Managing CBRN Safety and Security Affected by Cutting-Edge Technologies*, 141-177.

Akmal, S., Talha, M., Faisal, S. M., Ahmad, M., & Khan, A. K. (2023). Perceptions about FinTech: New evidences from the Middle East. *Cogent Economics & Finance*, *11*(1), 2217583.

Cosenza, E., Del Vecchio, C., Di Ludovico, M., Dolce, M., Moroni, C., Prota, A., & Renzi, E. (2018). The Italian guidelines for seismic risk classification of constructions: technical principles and validation. *Bulletin of Earthquake Engineering*, *16*, 5905-5935.

De Vries, H., Bekkers, V., & Tummers, L. (2016). Innovation in the public sector: A systematic review and future research agenda. *Public administration*, *94*(1), 146-166.

Dong, Y., Miraglia, S., Manzo, S., Georgiadis, S., Sørup, H. J. D., Boriani, E., Hald, T., Thöns, S., & Hauschild, M. Z. (2018). Environmental sustainable decision making–The need and obstacles for integration of LCA into decision analysis. *Environmental Science & Policy*, *87*, 33-44.

Duarte Alonso, A., Kok, S., & O'Brien, S. (2020). Brexit, the wine sector and organisational resilience: an exploratory study of Spanish Wineries. *Review of international business and strategy*, *30*(3), 301-322.

Faisal, K., Khan, A. K., & Al-Aboud, O. A. (2018). Study of Managerial Decision Making Linked to Operating and Financial Leverage. *International Journal of Accounting and Finance Research*, *7*(1), 139-143.

Faisal, S. M., & Khan, A. K. The Empirical Evidence of Oil Market Volatility and Other Macroeconomic Variables: A Study in Saudi Arabia.

Faisal, S. M., & Khan, A. K. (2019a). Depreciation of Indian Currency in the current economic scenario. *International Journal of Economic Research*, *16*(1), 91-97.

Faisal, S. M., & Khan, A. K. (2019b). Islamic banking: concept, challenges and proposed solution. *Asian Journal of Multidimensional Research (AJMR)*, *8*(2), 187-194.

Faisal, S. M., & Khan, A. K. (2021). The effect on pricing strategies in the process of strategic decision making in view of cost of produced goods. *Independent Journal of Management & Production*, *12*(7), 1705-1727.

Faisal, S. M., Khan, A. K., & Akmal, S. M. (2021). Social-Psychological and Economic Impact of Covid-19 in Indian Lifestyle: An Empirical Study. *Linguistica Antverpiensia*, 3572–3578-3572–3578.

Faisal, S. M., Khan, A. K., & Al Aboud, O. A. (2018). Estimating beta (β) values of stocks in the creation of diversified portfolio-a detailed study. *Applied Economics and Finance*, *5*(3), 89-99.

Harris, T., Tucker, J. D., Li, B., & Shand, L. (2021). Elastic depths for detecting shape anomalies in functional data. *Technometrics*, *63*(4), 466-476.

HASHIM, A., FAISAL, S. M., & KHAN, A. K. AN EMPIRICAL JOB SATISFACTION ANALYSIS IN THE BANKING SECTOR OF INDIA.

Hashim, A., Faisal, S. M., & Khan, A. K. (2022a). An Intense bibliographical study of job satisfaction theories in the private vis-a-vis public sector of banks. *World Wide Journal of Multidisciplinary Research and Development*, *8*(02), 125-128.

Hashim, A., Faisal, S. M., & Khan, A. K. (2022b). A time-series analysis of economic growth in the context of Indian Economy. *Integrated Journal for Research in Arts and Humanities*, *2*(2), 9-14.

Hashim, A., Faisal, S. M., & Khan, A. K. (2023). Analysis of green supplier using ARAS model integration in the decision-making process. *Journal of Environmental Impact and Management Policy (JEIMP) ISSN: 2799-113X*, *3*(03), 1-14.

Khalid, W. E. O., Faisal, S. M., & Khan, A. K. Effect of the economic performance of financial statements on raising levels of accounting conservatism.

Khalid, W. E. O., Faisal, S. M., & Khan, A. K. Role of Business Intelligence in Actuarial Accounting to Enhancing Predict Banking Risks.

Khan, A., & Faisal, S. (2018). Role and significance of FDI (outward) in Indian perspective an analysis: Post demonetization period. *J Account Mark*, *7*(276), 2.

Khan, A. K. (2019). Impact of demonetization on outwards foreign direct investment of India-Special reference to Asian countries. *SUMEDHA Journal of Management*, *8*(1), 23-42.

Khan, A. K., Al Aboud, J., & Faisal, S. M. (2018a). An empirical study of technological innovations in the field of accounting-boon or bane. *Business & Management Studies*, *4*(1), 51-58.

Khan, A. K., Al Aboud, O. A., & Faisal, S. M. (2018b). Muamma (conundrum) of Riba (Interest and Usury) in Major Religions in General and Islam in Particular. *The International Journal of Social Sciences and Humanities Invention*, *5*(2), 4438-4443.

Khan, A. K., & Faisal, S. M. (2020). The Bearing on Indian Frugality and Predicting of Average Crude Oil Rates since 1991 â€“A Study. *Management Dynamics*, 01-14.

Khan, A. K., & Faisal, S. M. (2021). Measuring Learning Outcome and Impact: An evident Jazan University, Saudi Arabia. *Arabia*, *1*(8), 16-23.

Khan, A. K., & Faisal, S. M. (2023). The impact on the employees through the use of AI tools in accountancy. *Materials today: proceedings*, *80*, 2814-2818.

Khan, A. K., Faisal, S. M., & Aboud, O. A. A. (2018). An analysis of optimal inventory accounting models–pros and cons. *European Journal of Accounting, Auditing and Finance Research*, *6*(3), 65-77.

KHAN, A. K., SULIMAN, E. M., KHALID, W., & FAISAL, S. M. THE FUTURE: ARTIFICIAL INTELLIGENCE'S PROFOUND IMPACT ON ACCOUNTING AND SOCIETY-ANTICIPATING JOB MARKET DYNAMICS AND EVOLVING SKILL REQUIREMENTS FOR ACCOUNTANTS.

Mohammad, K. (2019). Depreciation of Indian Currency in the current economic scenario. *International Journal of Economic Research*, *16*, 0972-9380.

Moser, A., & Korstjens, I. (2018). Series: Practical guidance to qualitative research. Part 3: Sampling, data collection and analysis. *European journal of general practice*, *24*(1), 9-18.

Nassani, A. A., Yousaf, Z., Grigorescu, A., Oprisan, O., & Haffar, M. (2023). Accounting Information Systems as Mediator for Digital Technology and Strategic Performance Interplay. *Electronics*, *12*(8), 1866.

Naviaux, R. K. (2020). Perspective: Cell danger response Biology—The new science that connects environmental health with mitochondria and the rising tide of chronic illness. *Mitochondrion*, *51*, 40-45.

Oláh, J., Aburumman, N., Popp, J., Khan, M. A., Haddad, H., & Kitukutha, N. (2020). Impact of Industry 4.0 on environmental sustainability. *Sustainability*, *12*(11), 4674.

Paterakis, N. G., Erdinç, O., & Catalão, J. P. (2017). An overview of Demand Response: Key-elements and international experience. *Renewable and Sustainable Energy Reviews*, *69*, 871-891.

Schulte, J., & Hallstedt, S. I. (2018). Company risk management in light of the sustainability transition. *Sustainability*, *10*(11), 4137.

Talha, M., Alenezi, M., Faisal, S. M., & Khan, A. K. (2023). Integrated Study of Ethical and Economic Efficiency of Society's Perception of Corporate Social Responsibility in India. In *Artificial Intelligence and Transforming Digital Marketing* (pp. 1093-1105). Springer.

Talha, M., Faisal, S. M., & Khan, A. K. (2024). Shariah Law in Commercial Banking and Stock Market: Recent Development, Challenges and Practices. *International Journal of Religion*, *5*(6), 620-630.

Tasdemir, C., & Gazo, R. (2018). A systematic literature review for better understanding of lean driven sustainability. *Sustainability*, *10*(7), 2544.

van Winsen, F., de Mey, Y., Lauwers, L., Van Passel, S., Vancauteren, M., & Wauters, E. (2016). Determinants of risk behaviour: effects of perceived risks and risk attitude on farmer's adoption of risk management strategies. *Journal of Risk Research*, *19*(1), 56-78.

Weaver, C. P., Lempert, R. J., Brown, C., Hall, J. A., Revell, D., & Sarewitz, D. (2013). Improving the contribution of climate model information to decision making: the value and demands of robust decision frameworks. *Wiley Interdisciplinary Reviews: Climate Change*, *4*(1), 39-60.

Zaman, S., Arshad, M., Sultana, N., & Saleem, S. (2021). The effect of family business exposure on individuals' entrepreneurial intentions: an institutional theory perspective. *Journal of Family Business Management*, *11*(4), 368-385.